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From Victim to Survivor: A Multilayered Adaptive Mental Network Model of a Bully Victim

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Abstract. Peer victimization is usually addressed with hazardous short and long term effects. Social surroundings and cyber technology act as a fertile ground for perpetrators to target victims. Fragile and lonely people are often targeted by aggressors or bullies who may make them feel like a 'loser'. This results in their withdrawal from society and can result in suicidal or revenge thoughts. In this paper, we present a complex multi-layered adaptive mental network model based on cognitive and psychological literature. The network model is simulated for three type of victims: a) passive, b) assertive and c) ambivert using case studies. It can be used as a basis in classification and to provide support of the victims.

Keywords: Bully-Victim · Victim of aggressor · Multilayered adaptive mental network

1 Introduction

> "Bullying is pushing someone around and making them feel like a failure . . . if you are blackmailing or threatening them, that is bullying. . . . If it is playful teasing, no, but if you are hurting someone's feelings, yes." [1]

Cyber-technology expands bullying into the technological realm, where perpetrators use smart devices to target and cause an intentional harm to their victims. Most victims experience distress, along with frustration, anger, and sadness due to threat to their self-image. This can have long-lasting effect over the health and esteem of a person, and may even result in school violence or suicide [2, 3].

Bullying-victims are usually neurotic or submissive by nature [4], which makes them the targets and lead them to withdraw and avoid bullies. They are usually not extrovert, as they are not much social or outgoing, and due to their shy and isolated nature recurrence of aggression is almost inevitable [4]. If victims are ambivert by nature (i.e. neither introverted nor extroverted) and they give their bully a 'stop' signal, it will not only help them to stop bullying [4] but also not to become aggressors. Different studies conducted in psychology and social science focused on behavioral traits of a victim [5, 6]. A study conducted in the domain of network modeling showed the mental processes of a

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victim that focuses on a fight or a flight reaction of a victim. However, in that reference, internalizing mechanisms or learning from experience and the personality of a victim was not considered [7].

This paper presents a biologically inspired complex multi-layered adaptive mental network addressing the personality of a victim, using first-order network layer for how learning impacts his or her internalizing behavior, and a second-order network layer affecting the learning rate and persistence of the learning. Section 2 explains the related work; while Sect. 3 presents the multilayered adaptive network model; Sect. 4 presents the simulation scenarios, and; Sect. 5 discusses the network model in comparison to available data; and Sect. 6 concludes the paper.

2 Related Work

Related work for a victim of an aggressor is presented in three streams: the cognitive literature, the behavioral literature, and by exploring the advancements in artificial intelligence in victim modeling and detection. There is vast literature available, which discusses the mental organization of a victim [6] and how his nature helps him to choose the right strategy to react to his aggressors [4].

While discussing the neurological or cognitive aspect, victims are identified by low self-esteem, making them susceptible to the bullies. Their cognitive attributions internalize bullying message as a threatening message (e.g., "people hate me"), which makes them feel threat and insecure. It leads to anxiety, which raises the cortisol levels in adults [6] and victim may get thoughts of taking revenge or committing suicide. Brain parts like the hippocampus (long-term/short-term memory), the amygdala (e.g., with the feeling of threat/anxiety) play the role for memory emotions and the motivations. These motivations along with the prefrontal cortex (PFC) involves in forming strategies to react to bullying. PFC is responsible to choose his own actions, with a complete ownership and learn to make long-term solutions/decisions.

An extravert person is not often bullied, so a victim is usually identified by his passive and submissive nature [8]. They appear lonely, shy and may show internalizing social difficulties like socially withdrawn [6]. They are lonely and afraid to tell anyone, because of lack of satisfaction and trust [9]. They have complaints of anxiety, anger or stress as few signs of high neuroticism [10] and usually do not retaliate bully. They experience low academic functioning and usually alienated as 'losers' [4, 6]. An ambivert victim react assertively for self-defense (e.g. an aggressive/assertive response depending on the context), whenever needed [6]. As this angry behavior of a victim is usually the result of threatened egotism, experienced by the victim [5], so his reaction may not only raise his self-confidence but also leave a positive message to bystanders(or other victims) to stand by him [6].

Machine learning techniques were also applied to detect cyberbullying traces, however, most of them relate by the bully perspective [11, 12], therefore support cant be aimed if a person reports him as a victim. Similarly, a temporal-causal study of a victim discussed flight and fight reaction of a victim [7]. However, there is no model designed, which explains the personality of a victim making him the target and his possible reactions.

3 A Multilayered Adaptive Mental Network Model of a Victim

This section presents a multilayered mental network model for a victim of an aggressor using a three layered reified architecture based on [13, 14], and the literature mentioned above. In this architecture, each layer signifies a specific role of the model. For example, Layer I indicates the base-model, while layer II and III represent the adaptive nature of the model, by plasticity and meta-plasticity respectively. The model is presented in Fig. 1, and the information of each layer is depicted in Table 1 and Table 2.

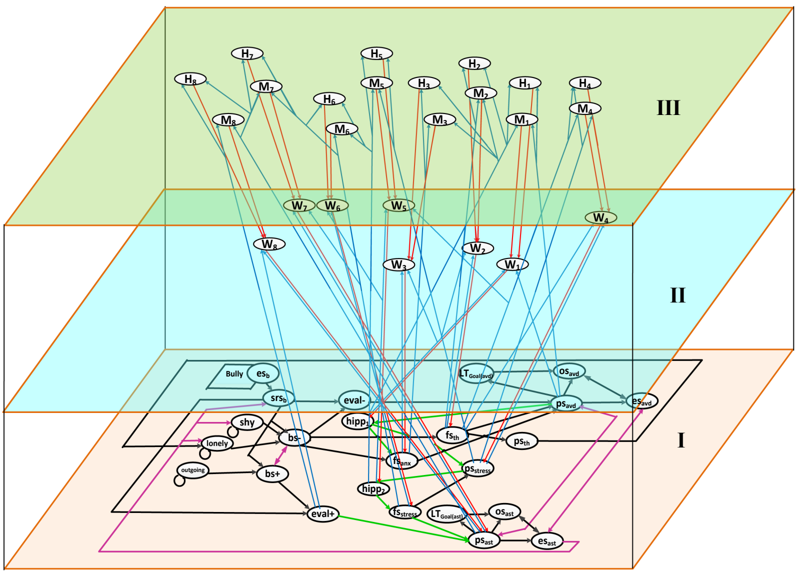


Fig. 1. Multi-layered reified network architecture for a victim. (Color figure online)

Layer I for the base network

The base layer (Layer I) contains the conceptual representation of the base model, based on the real-world scenarios by *states* and *connections*. A *connection* is a causal relationship between two states. For example, consider a causal relationship between states X and Y: $X \rightarrow Y$. All states along with X incoming to Y, have an influence over Y with a certain *speed*. Its *activation level* is the *aggregated impact* of all incoming states and varies by *connection weights* and *activations* of the incoming states. The *aggregated impact* is computed through different *combination functions* [15]:

Connection Weight $\boldsymbol{\omega}_{X,Y}$ indicates how strong state X influences state Y. The magnitude ranges between 0 and 1. A suppression effect on Y is categorized by a negative connection.

Speed Factor $\boldsymbol{\eta}_Y$ indicates how fast state Y can change its value (range: 0–1) due to a causal impact.

Table 1. Categorical explanation of states of the base model (Layer I).

Categories		References
Stimulus States:		*Stimulus is sensed and leads to representation:* [15]
es_b	Input from aggressor/bully	
srs_b	Sensory representation state of victim	
Person's Nature States:		*children who are socially isolated and exhibit other internalizing problems become increasingly victimized over time…* [4]
Shy	Shy nature	
Lonely	Lonely nature	
outgoing	Sociable nature	
Cognitive Attribution States:		*"Children are anxious, self-doubting, and tend to submit quickly"* [4]
bs_i	Belief state i =+/- (positive/negative)	
$eval_i$	Evaluation state i =+/-	
Avoidance (avd) and Assertive (ast) States:		*"the idea of internal simulation is that in a certain context (..goals and attitudes) preparation states for actions …in turn activate other sensory representation states"* [15]
ps_i	Preparation state i=avd/ast	
$LT_{Goal(i)}$	Long-term Goal i=avd/ast	
os_i	Ownership state i=avd/ast	
es_i	Execution state i=avd/ast	
Feeling and Memory States:		*it is assumed that the preparation for the response is also affected by the level of feeling … integration of emotion in preparation of actions (pg 239: Treur, 2016),* [6]
ps_i	Preparation state i=th (threat)/stress	
fs_i	Feeling state i=th/stress /anxiety(anx)	
$hipp_1$	Hippocampus: Brain region for avd	
$hipp_2$	Hippocampus: Brain region for ast	

Combination Function $\mathbf{c}_Y$(..) is chosen to compute the causal (aggregated) impact of all incoming states ($X_i : i = 1$ to N) for state Y. Certain standard combination functions are already defined, and can be used to compute aggregated impact of Y.

Layer I consist of 24 states, which presents a scenario of how a victim reacts when his self-image is in danger. Bullying (es_b) act as input to the model. It activates sensory representation state of the victim (srs_b). His personality plays an important role in deciding how to react to an aggressor/bully. A passive person (shy; lonely), internalizes (eval-) the stimulus (for example: "people don't like me") and avoids bully. However, an assertive victim will communicate his concerns to control the bullying environment. In Fig. 1 negative belief (bs-) internalize (eval-), along with the elevation of the feelings of threat (fs_{th}) and anxiety (fs_{anx}). They aggregate to prepare for avoidance behavior (ps_{avd}). Anxiety or threat usually arise due to past memories ($hipp_1$). He regulates (os_{avd}) himself by avoidance (es_{avd}), as a long term solution (LT_{Goal}). However, avoidance behavior results in social isolation ($ps_{th} \rightarrow$ lonely).

For an ambivert person, first he tries to act in passive manner, but feeling of threat stresses him (ps_{stress}: $fs_{th} \rightarrow ps_{stress}$) and he learns not to react passively (ps_{avd}), so he gets

Table 2. Explanation of States in Layer II and III.

States per Layer			References
Layer II (Plasticity /Hebbian learning for Omega states):			*First-order adaptation layer for plasticity by Hebbian learning* [15, 16]
W_1:	$W_{ps_{avd},\ hipp_1}$	for $ps_{avd} \rightarrow hipp_1$	
W_2:	$W_{hipp_1,\ fs_{th}}$	for hipp1 $\rightarrow fs_{th}$	
W_3:	$W_{hipp_1,\ fs_{anx}}$	for hipp1 $\rightarrow fs_{anx}$	
W_4:	$W_{fs_{th},\ ps_{stress}}$	for $fs_{th} \rightarrow ps_{stress}$	
W_5:	$W_{hipp_2, ps_{avd}}$	for $ps_{stress} \rightarrow hipp_2$	
W_6:	$W_{hipp_2,\ fs_{stress}}$	for $hipp_2 \rightarrow fs_{stress}$	
W_7:	$W_{fs_{stress},\ ps_{ast}}$	for $fs_{stress} \rightarrow ps_{ast}$	
W_8:	$W_{eval+,\ ps_{ast}}$	for eval+$\rightarrow ps_{ast}$	
Layer III (Meta-Plasticity/Learning rate and persistence):			*Second-order adaptation layer for meta-plasticity to control the Hebbian learning* [16]
M_i:	Persistence for $i = W_j$: $j = 1,\ldots,8$		
H_i:	Learning rate for $i = W_j$: $j = 1,\ldots,8$		

assertive (ps_{ast}). It is already activated if he or she is assertive by nature. Here his stress (ps_{stress}) activates learning and based on past experiences ($hipp_2$), his stress (fs_{stress}) is increased. As a result, he chooses assertive reaction as a regulation strategy, knowing (os_{ast}) his long-term goals (LT_{Goals}). This strategy helps him decrease shyness and his loneliness. Here black horizontal connections indicate a positive incoming connections to a state. The adaptive connections are represented by green horizontal connections, while purple horizontal connections indicate suppression of a state from an incoming connection.

Layer II for First-Order Network Adaptation

This layer has eight states based on adaption (Hebbian Learning), indicated by omega states W_i (where $i = 1$ to $8 \Leftrightarrow$ eight green colored connections at Layer I (Table 2)). The involved states act as presynaptic and postsynaptic states for a specific connection. For example, consider state W_1 (also denoted by $W_{ps_{avd},\ hipp_1}$), which is responsible for connection $ps_{avd} \rightarrow hipp_1$, ps_{avd} and $hipp_1$ act as presynaptic and post-synaptic states for learning. For more details about the Hebbian learning principle in network-oriented modeling, see [14, 15].

Layer III for Second-Order Network Adaptation

Layer III adds an abstraction level to learning behavior of states at layer II. Here, 16 meta-plasticity related states: M_i and H_i are presented. The former indicates persistence, while the latter specify the learning rate for $i = W_1$ to W_8 states in Layer II. For example, M_1 (also denoted as M $W_{ps_{avd},hipp_1}$), controls the persistence of W_1/$W_{ps_{avd},hipp_1}$ $W_{ps_{avd},hipp_1}$

at Layer II, with the incoming connections (blue) from the states ps_{avd} and $hipp_1$ respectively, and along with H_1 it suppresses W_1 (red connection from M_1 to W_1 state).

For the computation of impacts of states, we used three type of combination functions (Fig. 1) which are:

a) For 9 states (es_b; outgoing; bs−; bs+; eval+; $LT_{Goal(avd)}$; $LT_{Goal(ast)}$; os_{avd}; os_{ast}), we used the Euclidian function, with order $n>0$ and scaling factor λ as the sum of connection weights of a particular state:

$$\mathbf{eucl}_{n,\lambda}(V_1, \ldots, V_k) = \sqrt[n]{(V_1^n + \ldots + V_k^n)/\lambda}$$

b) For 31 states ($srs_{s,b}$; shy; lonely; eval-; $hipp_1$; $hipp_2$; fs_{th}; fs_{anx}; fs_{stress}; ps_{avd}; ps_{ast}; ps_{th}; ps_{stress}; es_{avd}; es_{ast}; H_i; M_i $i = 1$–8), **alogistic** function (positive steepness $\boldsymbol{\sigma}$ and threshold $\boldsymbol{\tau} < 1$) was used:

$$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k) = [(1/(1 + e^{-\sigma(V_1 + \ldots + V_k - \tau)})) - 1/(1 + e^{\sigma\tau})]\,(1 + e^{-\sigma\tau})$$

where each V_i is the single impact computed by the product of weight and state value: $\omega_{X,Y}\, X(t)$.

c) Lastly, for the 8 adaptation states (W_1; W_2; W_3; W_4; W_5; W_6; W_7; and W_8) we used Hebbian learning principle defined by the following combination function:

$$\mathbf{hebb}_{\mu}(\mathrm{V}_1, \mathrm{V}_2, \mathrm{W}) = V_1 V_2 (1 - W) + \mu W$$

Mathematically, a reified-architecture based model is represented as [14]:

1. At every time point t, the activation level of state Y at time t is represented by $Y(t)$, with the values between [0,1].
2. Single impact of state X on state Y at time t is represented by $\mathbf{impact}_{X,Y}(t) = \omega_{X,Y}\, X(t)$; where $\omega_{X,Y}$ is the weight of connection $X \rightarrow Y$.
3. Special states are used to model network adaptation based on the notion of reification network architecture. For example, $\mathbf{W}_{X,Y}$ represents an adaptive connection weight $\omega_{X,Y}(t)$ for the connection $X \rightarrow Y$, while $\mathbf{H}_Y$ represents an adaptive speed factor $\eta_Y(t)$ of state Y. Similarly, $\mathbf{C}_{i,Y}$ and $\mathbf{P}_{i,j,Y}$ represent adaptive combination functions $c_Y(.., t)$ over time and its parameters respectively. Combination functions are built as a weighted average from a number of basic combination functions $bcf_i(..)$, which take parameters $P_{i,j,Y}$ and values V_i as arguments. The universal combination function $\mathbf{c}^*_Y(..)$ for any state Y is defined as:

$$\begin{aligned}
&\mathbf{c}^*{}_Y(S, C_1, \ldots, C_m, P_{1,1}, P_{2,1}, \ldots, P_{1,m}, P_{2,m}, V_1, \ldots, V_k, W_1, \ldots, W_k, W) \\
&\ = W + S[C_1 \mathrm{bcf}_1(P_{1,1}, P_{2,1}, W_1V_1, \ldots, W_kV_k) + \ldots \\
&\quad + C_m \mathrm{bcf}_m(P_{1,m}, P_{2,m}, W_1V_1, \ldots, W_kV_k)]/(C_1 + \ldots + C_m) - W]
\end{aligned}$$

where at time t:

- variable S is used for the speed factor reification $\mathbf{H}_Y(t)$
- variable C_i for the combination function weight reification $\mathbf{C}_{i,Y}(t)$
- variable $P_{i,j}$ for the combination function parameter reification $\mathbf{P}_{i,j,Y}(t)$
- variable V_i for the state value $X_i(t)$ of base state X_i
- variable W_i for the connection weight reification $\mathbf{W}_{Xi,Y}(t)$
- variable W for the state value $Y(t)$ of base state Y.

4. Based on the above universal combination function, the effect on any state Y after time Δt is computed by the following *universal difference equation* as:

$$\begin{aligned}
Y(t + \Delta t) = {} & Y(t) + [\mathbf{c}*_Y (\mathbf{H}_Y(t), \mathbf{C}_{1,Y}(t), \ldots, \mathbf{C}_{m,Y}(t), \mathbf{P}_{1,1}(t), \mathbf{P}_{2,1}(t), \ldots, \\
& \mathbf{P}_{1,m}(t), \mathbf{P}_{2,m}(t), X_1(t), \ldots, X_k(t), \mathbf{W}_{X_1,Y}(t), \ldots, \mathbf{W}_{X_k,Y}(t), Y(t)) - Y(t)]\Delta t
\end{aligned}$$

which also can be written as a *universal differential equation*:

$$\begin{aligned}
\mathbf{d}Y(t)/\mathbf{d}t = {} & \mathbf{c}*_Y (\mathbf{H}_Y(t), \mathbf{C}_{1,Y}(t), \ldots, \mathbf{C}_{m,Y}(t), \mathbf{P}_{1,1}(t), \mathbf{P}_{2,1}(t), \ldots, \mathbf{P}_{1,m}(t), \\
& \mathbf{P}_{2,m}(t), X_1(t), \ldots, X_k(t), \mathbf{W}_{X_1,Y}(t), \ldots, \mathbf{W}_{X_k,Y}(t), Y(t)) - Y(t)
\end{aligned}$$

We simulated our model using a dedicated Reified Network Engine [16], by providing input of the characteristics of the network model represented by role matrices. A role matrix is a compact specification with the concept of the role played by each state with a specified type of information. Detailed information for our model can be found online [13, 17].

4 Example Scenarios

Reaction of a victim of an aggressor depends mostly on the personality of a victim a) Passive, or b) Assertive, or c) Ambivert. In this section, we present the simulation scenarios of three strategies by victim based upon his nature:

4.1 An Avoidance Strategy (Passive Reaction)

To understand this strategy, let's consider a social environment, in which there is a peer who is being victimized by calling bad names. His reaction can be like "They called me bad names, and I didn't know what else to do than walk away from them". Or "I started to go together with Sara and Joy after a month in the new class. However, after some weeks they began to run away from me during breaks, laughing and whispering and hiding different places (pause). That is why I am alone." [18]. These type of reactions are common in victims, due to their passive nature.

While looking into the simulation results in Fig. 2, when es_b is 1 and shy and lonely is also active, then srs_b is activated along with bs− (magenta), his internalization (eval-) gets active at $t = 10$. bs− makes the feelings of threat (fs_{th}) and anxiety active (purple-bold) and causes an avoidance reaction (ps_{avd}; es_{avd}) to elevate along with regulation states ($LT_{Goal(avd)}$; os_{avd}). Feeling of threat fs_{th} (pink-bold) increases and makes him stressed (blue curve: ps_{stress}) at $t = 200$, however, as his anxiety becomes much higher, so he choose avoidance strategy (e.g. upping the privacy on social media)

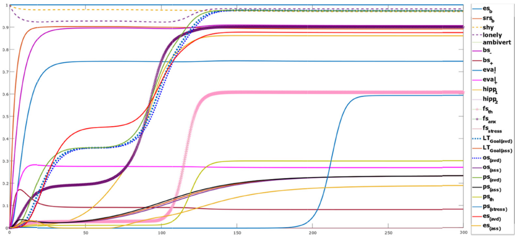


Fig. 2. The victim chooses an avoidance strategy but feels stressed. (Color figure online)

Looking into the plots of Layer II and III (Fig. 3), learning behavior can be seen for M_i, H_i and W_i where $i = 1$ (pink), 2 (purple), 3 (brown), and 4 (green). W_5 (red) arises, however it doesn't play its role except the victim has stress (ps_{stress}). Rest of omega states don't show any dynamics for $i = 6$ to 8. Therefore, learning rates (H_i) and persistence (M_i) are constant, and the corresponding W_i are zero. For example, H_8 and M_8 are constant, thus $W_8/W_{eval+,\, ps_{ast}}$ remains zero showing that there is no learning overtime. It would not be wrong to say that all omega states associated to assertive behavior will stay low along with constant M and H, as the person is not assertive by nature.

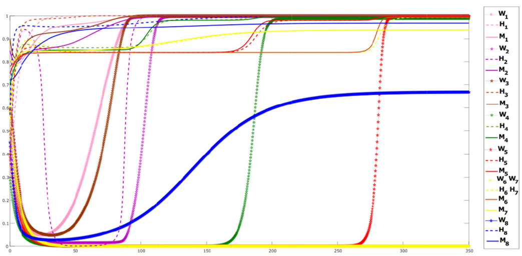
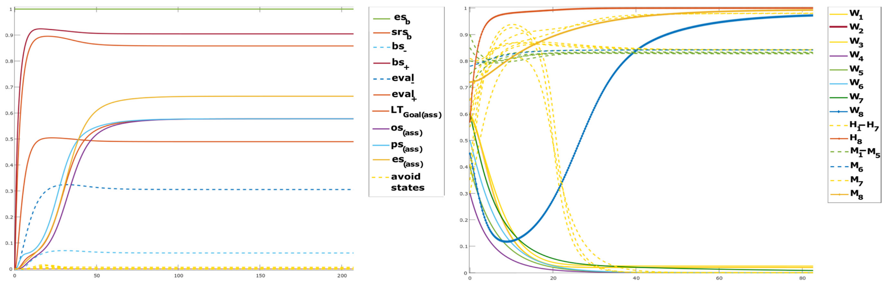


Fig. 3. Plots of Layer II and III. No learning except for the states W_1 to W_4 (shown by asterisk). (Color figure online)

4.2 An Assertive Strategy (Assertive Reaction)

Although this is a rare case but, to understand this strategy, consider the scenario when a new boy enters in a social circle, where all peers are not well-aware of his nature and if they try to piss him off. He gives them a 'Stop' signal, without hurting own esteem.

Considering the simulation in Fig. 4a, an assertive victim has his positive belief (bs+) as high, which activates the states related to the assertive behavior (ps_{ast}; es_{ast}; $LT_{Goal(ast)}$; os_{ast}), making the avoidance strategy related states (yellow-dotted) low (=0). Here eval+(orange) is followed by bs+ at time point $t = 10$. Then ps_{ast} (blue) is activated along with well-aware long-term goals with $LT_{Goal(ast)}$ (orange) and os_{ast} (purple), and es_{ast} (yellow)



(a) (b)

Fig. 4. a) An outgoing reaction towards a bully. b) plots of Layer II and III. Learning is only observed in assertive behavior (i =8: bold). (Color figure online)

Plots of Layer II and III (Fig. 4b), shows that only W_8/$W_{eval+,\,psast}$ has learning (time point t >25). All M_i and H_i ($i = 1$ to 7) stays constant, i.e. between 0.8 to 0.9, thus no learning is observed for W_i. However, H_8 (red), M_8 (mustard) and W_8 (blue) show the learning dynamics. So the avoidance behavior is not observed while being assertive.

4.3 Change of Strategy (Ambivert Reaction)

An example scenario can be a peer, who is not very outgoing by nature except his social circle. When targeted, he initially tries to avoid the bully by ignoring his dirty talk, or avoiding to confront him. However, when this doesn't stop him, and he feel threatened he talks to his elders and then the situation gets better. It is an expected reaction and by this, his self-confidence is raised, and shyness is reduced. As a result, bullying is stopped and self-worth is maintained.

While looking into the simulation explained in Fig. 5, we can see an ambivert victim who, tries to avoid bully first. In this case, all states related to the avoidance behavior get activated during time point $t = 0$–50. However, as the time passes, threat to his ego (fs_{th}: purple) causes stress (ps_{stress}:yellow).This leads to change his strategy, so he switches from avoidance to an assertive reaction at $t = 50$–120. Assertiveness (shaded region with ps_{ast}; $LT_{Goal(ast)}$; os_{ast}; es_{ast}) gets high and suppress the avoidance related states (ps_{avd}; $LT_{Goal(avd)}$; os_{avd}; es_{avd}), along with the avoidance related feelings (fs_{th}; fs_{anx}). Eventually, his ego/self-confidence (black dotted: bs+) gets higher, and shyness (golden dotted) or loneliness (dark green dotted) are lowered (0 and 0.9 respectively). Assertive reaction gets low $t = 250$, as bully is handled. Here, it is to be noted, that in contrast with shyness (shy), loneliness doesn't drop to 0 (0.85 at $t = 310$). The reason is the dynamics of his nature, that is he gets assertive only when needed.

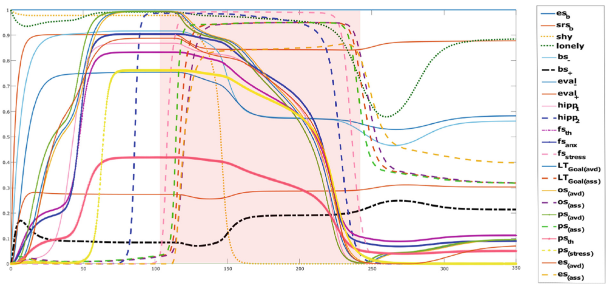


Fig. 5. Victim chooses avoidance strategy first and then an assertive strategy (shaded region). (Color figure online)

Plots of Layer II and III (Fig. 6), show that all W states learned over the time. But around time point $t = 110$, state W_8 (yellow) learns even faster and reach its maximum value. As a result, this causes the rest of the W states to get suppressed, and then it remains equilibrium showing that he learned how to react in an assertive manner.

In each of the simulation experiments (Fig. 2 to Fig. 5) presented in this section, it is shown that each pattern is reaching an equilibrium as each state doesn't show further dynamics.

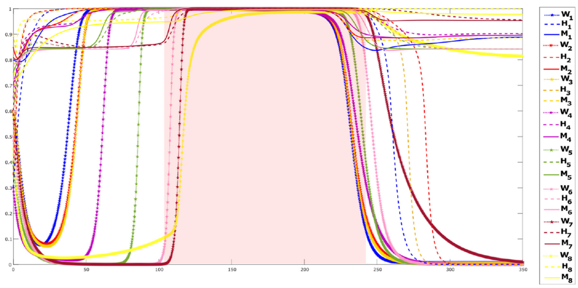


Fig. 6. Plots of Layer II and III. Learning of all states (W_1 to W_8) over time (Color figure online)

5 Conclusion

A biologically inspired multilayered adaptive network model of a victim of an aggressor, is presented based on cognitive, psychological and social literature, using a multilayered reified architecture. Hebbian learning effects are also observed. If a person is shy and lonely, loneliness increases over the time by his avoidance reaction. Also, it shows that threat to ego, increases the stress over the time, to make the victim assertive. In future, we aim to study the model with respect to related data, and to devise support strategies and therapies to the victim.

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